NAVAL POSTGRADUATE SCHOOL
Monterey, California

THESIS

INTERMEDIATE TERM FORECASTING
TECHNIQUES FOR MANAGEMENT

by

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June 1984

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REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER	2. GOVT ACCESSION NO. / 3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Intermediate Term Forecasting Techniques for Management	5. TYPE OF REPORT & PERIOD COVERED Master's Thesis June 1984
	6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) David L. Herring	8. CONTRACT OR GRANT NUMBER(s)
9. PERFORMING ORGANIZATION NAME AND ADDRESS Naval Postgraduate School Monterey, California 93943	10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS Naval Postgraduate School Monterey, California 93943	12. REPORT DATE June 1984
	13. NUMBER OF PAGES 84
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)	15. SECURITY CLASS. (of this report)
	15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Forecasting
Budgets
Commodities

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

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computer software employably on inexpensive microcomputers. It is concluded small businesses can affordably obtain moie accurate commodity price budgets through the use of ARIMA forecasts.

Intermediate Term Forecasting Techniques for Management

by

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MASTER OF SCIENCE IN MANAGEMENT

from the

NAVAL POSTGRADUATE SCHOOL
June 1984

ABSTRACT

Autoregressive Integrated Moving Average (ARIMA) forecasts are made for the prices of a variety of commodities one year into the future in an attempt to determine if improved budget accuracy is possible for small businesses dependent upon commodities for the production of goods or services. An average forecast error of less than seven percent is obtained using commonly available ARIMA computer software employable on inexpensive microcomputers. It is concluded small businesses can affordably obtain more accurate commodity price budgets through the use of ARIMA forecasts.

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I. INTRODUCTION

A. UNCERTAINTY

Business and government managers involved in the production of goods or services must deal with uncertainty. They must contend with a multitude of variables, the magnitude of which are unknown and may only be estimated; variables which ultimately affect the profitability (or budget, in the case of government managers) of their corporations or agencies. [1] The list of unknowns is both large and varied. Most are interdependent and affect one another either directly or indirectly. Variables such as economic conditions, inflation, product market share, price of production or service required commodities or supplies, cost of goods sold, revenues, inventory costs, and many others are all important. Their magnitudes determine the profitable conduct of business. Considerable effort is therefore directed toward making an accurate determination of their actual value, and, when possible, an accurate estimation of their future value. Sophisticated accounting procedures determine and allocate production costs, market research is conducted in order to estimate demand for a new product, and sales, revenue and cost projections are made. These and other estimates are made in an attempt to reduce risk and increase profit.

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[1] Although government agencies are non-profit, they too are operated by budgets, and expenses or expenditures in excess of budget are similar to corporate losses while those totaling less than budget may be thought of as profit. Corporation and government managers also face many of the same uncertainties. Therefore, the terms manager, profits and losses should henceforth be considered for the most part as applicable to both corporations and government agencies and the executives or managers of each.

B. RISK AVERSION

Corporations must, of course, operate with risk. Uncertainty entails risk and business is conducted in an uncertain and therefore risk filled environment. Every manager must therefore deal with uncertainty, must evaluate and incur risk. A firm may come to success, outpace competitors, because of the ability of its managers to properly evaluate a situation and take an action - incur risk - based upon that evaluation. Yet corporations are risk averse. They will, for example, pay insurance premiums which are well in excess of the expected value of the probable loss involved in the possible destruction of buildings or other assets by fire or flood. Corporations do not seek risk, they are averse to it. Risk means subjection to possible danger or harm. No corporation seeks that. Certain profit would be preferred but, as has been observed, corporations, of necessity, function in an uncertain and risk filled environment. Most risk cannot be negated or shifted by purchase of insurance. The best that can be done is to reduce risk by reducing uncertainty.

Corporations must incur risk to survive. Many firms ultimately fail because of their refusal to incur risk, to innovate, seek new products and new markets. This may on first sight seem paradoxical: Firms are risk averse yet they must incur risk or perish. Yet it is most logical. If risk must be incured, then best to reduce it as much as possible.

The fewer the unknowns, the less uncertainty involved in any given corporate situation, the better the chance for accurate managerial planning, budgeting, etc., and the greater the probability for success and profit. This applies equally well to long and short range planning and to day to day operations. If firms may become successful by innovative risk taking behavior or action, one may be assured such

action is undertaken only after careful study and planning have reduced the uncertainty and risk involved to the lowest possible minimum.

In any given situation in which a number of alternative actions are available, each with a possibility of achieving a desired outcome, the more that is known about each possible action and the probabilities of its attendant outcomes - i.e., the less uncertainty present - the less risk will be present. Conversely, the more uncertainty involved the greater the probability of failure or of obtaining an unfavorable outcome; i.e., the greater the hazard or risk. Clearly then, the diminuation of risk by the reduction of uncertainty is a goal of near universal applicability in the corporate environment. So much is common sense.

C. FORECASTING

One tool for diminishing risk is forecasting. To accurately predict the future value of any of the aforementioned interdependent variables attendent to business production or service ventures is to reduce risk by reducing uncertainty. A reliable and predictably accurate forecast facilitates accurate planning and budgeting which subsequently benefit profit.

1. Predictability and Effect

Some variables fluctuate through so small a range of value little more is needed to forecast their future value than to measure their present value. Others vary over a wide range that makes accurate estimation of future value an involved and difficult task. Likewise, a wide range of effect occurs between variables. A minor change in one can have a profound effect on other variables or on profit while

a larger shift in another may be of lesser consequence. The desired level of forecast accuracy and the ease of variable predictability is therefore dependent upon the characteristics of the variable or variables involved.

2. Statistics, Forecasting and the Computer

Statistics is devoted in large part to forecasting. Many statistical models have been developed for forecasting, each with its own particular strengths and weaknesses, and each best suited to specific data types. No one forecasting model has proven superior in all situations with all types of data.

Statistics is a complex, rigorous and demanding field of study requiring of its practitioners a broad knowledge of mathematics in addition to many mathematical and statistical principals and techniques specific to the field. Although statistics courses are included in the curriculum of most undergraduate level business colleges, the average graduate would not in past have been capable of making the voluminous calculations necessary to even the most rudimentary of forecasting techniques. Such calculations would likely have required the efforts of a trained statistician or the retention of a forecasting consultant firm. This would not present a problem to large organizations with budgets sufficient for the hiring of such specialized personnel or consultants. Many smaller businesses and government agencies are, however, unable to afford a full-time statistician or a forecasting firm - the services of which can cost from $10,000 to $54,000 per year and higher [Ref. 1]. They therefore do not attempt forecasting, other than the simplest of projections based mainly upon managerial experience.

Computers have changed that. Small businesses unable to hire statisticians or forecasting consultants no longer

need do without forecasts. The wide availability of business computers and the requisite software for statistical analysis and forecasting now make forecasting available to small businesses without the services of a statistician [Ref. 2]. A wide range of user friendly software programs are available covering virtually the full spectrum of statistical forecasting models. Their ease of use should allow operation by most business school graduates with a basic knowledge of statistics. [2] Programs are available for accounting, budgeting, inventory management, sales projections, internal rate of return, and many other functions. Computer retail outlets stand ready to sell the computer and programming necessary and even offer how-to classes for the uninitiated [Ref. 3].

D. PRICE UNCERTAINTY

Many businesses, of all sizes, are dependent upon one or more commodities for the production of products or services. The past twenty years have witnessed economic cycles which have consecutively entailed periods of economic expansion and inflation, followed by recession and deflation or recession and stagflation, followed by yet another period of expansion [Ref. 4]. In such an environment commodity prices can fluctuate over a sufficiently wide range to materially affect the earnings of a firm employing one or more such commodities in the production of goods or services. Price fluctuations showing a high which is 33% to 50% and sometimes as much as 100% above the low can occur within a years time for widely traded commodities on major exchanges [Ref. 5].

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[2] For example, see IBM's catalogue of software for personal size computers, available at any local retail computer outlet, nationwide, that carries IBM products.

E. ALTERNATIVES

Businesses dependent upon commodities which experience a wide range of prices have a number of alternatives available in which to handle their purcases:

1. Do not attempt to forecast commodity price changes. Buy as needed, in accordance with economic order quantity (EOQ) [3] - assuming storable commodities - and make no projections of the impact of possible commodity price changes on the cost of goods sold and profits. [4]

2. Forecast price changes. Buy as needed, in accordance with EOQ, but incorporate forecast commodity price changes into the budget in advance of purchases.

3. Hedge commodity price risk through the simultaneous purchase and sale of futures contracts [Ref. 5].

4. Insure future price by purchase of commodities futures contracts.

5. Forecast future prices and:

    a. Purchase commodities futures contracts whenever forecast price is greater than futures contract price.

    b. Forego purchase of futures contracts and buy commodities as needed in accordance with EOQ whenever forecast price is less than futures contract price.

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[3]The economic order quantity treats demand, item cost, ordering costs, and storage costs. It minimizes inventory cost by equalizing order and storage costs.

[4]Only storable commodities will be addressed in this thesis.

Clearly, of the alternatives listed, the last is most desirable (assuming accurate and reliable forecasts are possible):

If purchases are made as needed with no effort to forecast and incorporate price changes into the budget in advance of their occurance, the budget will be inaccurate should substantial commodity price changes occur. Earnings will likewise be affected.

Incorporating accurate forecasts (again, assuming them possible) into the budget without the purchase of commodities futures contracts allows a more accurate budget but foregoes the benefit of futures contracts upon costs.

Simply buying commodities futures contracts insures the future price which assures a correct budget regarding cost of commodities. However, it subjects the firm to earnings risk. If prices are locked in by purchase of futures contracts and prices fall below contract price an opportunity for a lower available price is lost.

Hedging can reduce price risk, but the opportunity offered by lower prices is diminished. Hedging strategies can be quite complicated and are made even more difficult if the required future quantities are unknown.

Accurate forecasting, in conjunction with the purchase of open positions in commodities futures contracts, offers the most benefit. Forecast prices can be incorporated into the budget. Costs may be lowered by the purchase of futures contracts when predicted prices are greater than futures prices. Savings can also be made by foregoing purchase of futures contracts when forecast prices are less than futures contract prices.

F. PURPCSE

It is the purpose of this thesis to examine the feasibility of forecasting the short to medium term (three months to one year) price of storable commodities, with an average accuracy of ten percent or less for a one year forecast, using commonly available computer software, employable with a minimum of training, and in the absence of specialized statistical expertise. Ten percent is chosen as the goal for accuracy because it should at minimum gain an ability for greater accuracy in budgeting (the second of the above alternatives) than is available without forecasts. This in itself is a worthy initial goal. Then, if accuracy of five percent or better can be achieved, further examination of the use of futures contracts in conjunction with forecasts will be in order.

As noted earlier, a wide variety of statistical computer programs are available which are capable of analysis and forecasting of many types of data sets. Commodity traders and forecasting consultant firms use computer programming in their determination of commodity price forecasts [Ref. 6]. Although this may be thought as encouraging to the intent of this paper, it must be noted professional traders and consultants have a great deal of market experience, knowledge, and research at their disposal, in addition to computer programs.

Before proceeding to selection of an appropriate forecasting method, an examination needs to be made of a hypthosis which is directly related to any effort toward predicting future prices on a well traded and regulated market: The Efficient Market Hypthosis.

II. THE EFFICIENT MARKET HYPTHOSIS

The Efficient Market Hypthosis (EMH) addresses the possibility of earning profits in excess of those expected by the market through the incorporation of any system based upon publicly held information. It maintains no such system is possible and implies no system can consistently predict future market prices that are both valid and unequal to those prices expected by the market. Since historical prices are public information and are the data set this thesis will employ in an attempt to predict future market prices, an examination of the hypthosis is therefore in order.

A. EFFICIENT MARKETS

A market is efficient if the prices of its stocks, commodities or securities fully reflect all available information. Using available information, if any group of market participants thought prices were too low, their buying would force prices up. Conversely, if any group thought prices too high, their selling would force prices down. As new information occurs it is incorporated into the market and a new equilibrium price, based upon expected return, is established. Under such conditions the only price changes occurring would be the result of new information, and tomorrow's expected price, given today's price, is today's price. That is, at any given point in time the market will have incorporated all available information into the price so that tomorrows price, in the absence of any new information, will be the same as today's price - withstanding inflation. Since there is no reason to expect new information occurs on

a non-random basis, period to period price changes should be random in nature and statistically independent of one another.

B. EFFICIENT MARKET HYPTHOSIS

The Efficient Market Hypthosis is treated at length in the literature and has been stated in many ways. A simple and general way of expressing it is:

> A market is efficient with respect to information set θ at time t if it is impossible to make economic profits by trading on the basis of information set θ_t at time t. [Ref. 7]

By economic profits is meant the risk adjusted returns net of all costs, such as taxes or transaction costs, that are in excess of the equilibrium expected profits or returns.

C. HYPTHOSIS FORMS

The literature normally recognizes three distinct forms of the Efficient Market Hypthosis, the strong form, semi-strong form, and the weak form.

1. Weak Form

In the weak form of the Efficient Market Hypthosis, the information set θ_t is taken to be only the information contained in the past price history of the market to time t.

2. Semi-strong Form

In the semi-strong form the information set θ_t is held to contain all publicly held information about the market at time t. This includes all public knowledge regarding the market in particular and the national and world economic conditions in general, which, of course, includes the markets price history.

3. Strong Form

Several versions of the strong form appear in the literature. A good representation of the strong form may be made by subdividing it into the strong form and the extreme strong form.

a. Strong form

The strong form of the Efficient Market Hypthosis holds the information set Θ_t to contain all information held by any investor groups or professional fund managers at time t which might have access to information relevant to the market that is not publicly available.

b. Extreme strong form

In the extreme strong form of the Efficient Market Hypthosis, Θ_t is taken to include all information known to anyone at time t.

D. TESTS OF THE EFFICIENT MARKET HYPTHOSIS

Beginning with the weak form and progressing to the extreme strong form, the information set of each successive form includes all information contained in the form preceding it. Each form is therefore an element or subset of its successive form. That is:

weak $\subset$ semi-strong $\subset$ strong $\subseteq$ extreme strong form.

It follows that if any form of the hypthosis is proven correct, then all forms preceding it in this progression must also be correct. For example, if the extreme strong form is correct then all forms are correct.

This thesis hopes to predict future prices by an examination of historical prices. The weak form of EMH therefore pertains directly to the possible success of this effort. It

has been shown, however, that the proof of any EMH form also proves the weak form. A brief examination of each of the other forms will therefore also be made.

1. Strong Form

a. Extreme strong form

The extreme strong form of EMH is normally considered to be no more than a logical conclusion to the hypthosis. If the information set θ_t is considered to be information held by anyone it must include that held by corporate officers who are privy to changes in revenue and earnings, planned acquisitions, mergers and other information that directly affects the profit of the firm, long before that information becomes public. They thus have opportunity to act on monopolistic information before it becomes available to the public and is reflected in the market price, and therefore have opportunity to earn excess profits. Numerous laws designed to prevent corporate insiders from earning excess profits do, in fact, exist but are extremely difficult to enforce and are widely recognized as less than totally effective [Ref. 8] and [Ref. 9]. Ostensibly, the extreme form is not valid. It does, however, complete the hypthosis and may serve as a benchmark agaisnt which to measure the other forms.

b. Strong form

Recall, the information set θ_t of the strong form includes information held by groups of investment "professionals", individuals normally trained in economics and finance and with years of experience in the market. Additionally, their staffs often include researchers and analysts to aid in market analysis and forecasting.

The literature generally accepts that groups of professionals exist which are able to earn economic profits. It is virtually impossible, however, to discern what portion of a market professionals' performance derives from the availability of special information and what portion of "special information" is merely the product of a keener insight into publicly available information. Hence, a strict test of the strong form is impossible.

Not all "professionals" earn excess profits, however. One group of professionals, which has been the subject of some study, apparently does not. As a group, the managers of open ended mutual funds do not appear to match the markets performance. (See [Ref. 10] and [Ref. 11].) A mutual fund's performance is normally evaluated on its ability to earn profits in excess of a buy-the-market-and-hold strategy, adjusted for the given risk level of the fund. The criterion is normally the ability of funds to produce higher returns than some norm. Finding a "norm" against which to measure performance is a theoretical problem. If investors are risk averse and so must be compensated for any risks undertaken, then it becomes difficult to evaluate each fund relative to a norm which reflects its chosen level of risk. Major differences can therefore exist between results obtained in separate tests of a related area because of differing definitions or methods employed in treating risks. No general agreement seems to have been reached in the literature and tests of EMH are often criticized for their treatment of risk.

One study, of 115 open ended mutual funds, from 1945-1964, indicated mutual funds on average, when adjusted for risk, were unable to predict stock prices sufficiently well to enable them to beat a market buy-and-hold policy [Ref. 12]. This held also when fund returns were measured gross of management expenses, which indicates funds on

average did not quite even recoup their brokerage expenses. The average fund manager, making stock trades based upon his knowledge of market conditions and of corporations, the stock of which was offered on that market, would therefore have been better off to have followed a buy-and-hold policy as well. Such strategy should improve return by at least reducing brokerage expenses.

Investors in mutual funds allocate their investment choices to fund managers. Managers have little incentive to pursue a buy-and-hold policy since the investor could have followed that policy himself, at a lesser cost than through the use of a mutual fund. Also, pursuit of such a policy would be tacit admission on the managers part that he or she had not sufficient knowledge to beat that same self-employable strategy.

If it is admitted that market professionals are capable of earning excess profits, then open ended mutual funds appear to be a large and curious exception. One possible explanation for their performance relative to the market is their size. Mutual funds can control hundreds of millions of dollars worth of stock. Regulations require they hold no more than a small percentage of their total funds in any one stock. Funds therefore become so large and diversified as to be representative of the market they are trying to outperform. This is, in fact, the reason investors allocate their choices to mutual funds: such funds offer the small investor a diminishment of risk through diversification that could not otherwise be obtained.

2. Semi-strong Form

The semi-strong form version of EMH - where the information set θ_t is taken to be all publicly available information at time t - is the accepted paradigm of the Efficient Market Hypthosis. While the literature admits the

strong form is incorrect and contents itself with exceptions such as open ended mutual funds, it generally purports the semi-strong form to be correct. Yet, a sufficient number of rigorous studies exist to challange the semi-strong form of the hypthosis. The following studies appeared with others in a prominent financial journal in an issue dedicated to exceptions to the semi-strong form of the hypthosis:

> In his paper "Anomalies in Relationships Between Securities' Yields and Yield-Surrogates", Ball (1978) found that post-announcement risk adjusted abnormal returns are systematically non-zero, in the period following earnings announcements, in a fashion inconsistent with market efficiency [Ref. 13].
>
> Thompson (1978) found in his study, "The Information Content of Discounts and Premiums on Closed-End Fund Shares", that a trading rule based on discounts for closed-end funds, earned statistically significant abnormal returns of about 4% per year, from 1940-1971 [Ref. 14].
>
> Finally, Charest (1978) found abnormal returns available with respect to the markets reaction to changes in stock cash dividends. His study indicated prices of stocks on the New York Stock Exchange under-react to the announcement of dividend changes. A considerable period of time was necessary for the change to be fully incorporated into the stock prices, and abnormal returns were available in the interim. [Ref. 15]

Several other studies in the same issue also challanged the hypthosis, and the literature increasingly is offering further exceptions to the semi-strong form. (e.g., see also [Ref. 16] and [Ref. 17].)

3. Weak Form

The weak form of the Efficient Market Hypthosis (EMH), in which the information set θ_t contains only price history, is the foundation of EMH. The impetus for the development of a theory came from the accumulation of evidence that the behavior of common stock and other speculative prices might be approximated as a random walk. In 1953 Kendall examined weekly changes in 19 indices of British industrial share prices and commodity spot prices for cotton and wheat. After analysis of serial correlation between the prices he concluded: "The series looks like a wandering one, almost as if once a week the Demon of Chance drew a random number from a symetrical population of fixed dispersion and added it to the current price to determine next weeks price" [Ref. 18]. Faced with this and other evidence, economists felt compelled to offer a theory and the Efficient Market Hypthosis resulted. The weak form of EMH has been the subject of extensive testing. While early studies found some serial correlation or other dependance could be shown to exist between security or commodity prices, no trading rule based upon such dependence could be found which was capable of earning profits greater than a buy-and-hold policy. Curiously, sufficient dependence existed to fashion trading rules capable of earning excess profits for brokers - who pay only miniscule transaction costs - but not for investors who must pay normal transaction costs [Ref. 19]. After fairly extensive testing of the weak form much of the literature turned to an examination and testing of the semistrong form.

Yet the weak form is not without some rather serious detractors. The investment community has for many years included security and commodity analysts whose predictions of future price movements are based upon previous price

movements. Called technicians, these analysts contend prices move in cycles and trends that a trained observer can recognize and react to in sufficient time to earn excess profits. Unfortunately, their techniques all largely require interpretation on the part of the analyst and are themselves therefore difficult to analyse. No widely acceptable tests of the capabilities of market technicians as a group have been made, to date.

Later studies have, however, been made which found sufficient dependence or trends to enable profits in excess of buy-and-hold and to question the validity of the weak form of the hypthosis. The following are but a few of many such studies:

> Cootner's (1962) study of a group of 45 stocks from the New York Stock Exchange (NYSE) indicated individual stock prices are not independent and do in fact move in trends. He was able to design a trading rule based upon a 40 week moving average which had a net weekly gain 9.5% greater than buy-and-hold. [Ref. 20]

> A study by Alexander (1961) indicated stock prices do act in a random manner over time but a move in prices, once initiated, tends to persist. "In particular, if the stock market has moved up by x per cent it is likely to move up more than x per cent further before it moves down by x per cent." He concluded that statisticians and technicians were both correct. Stock prices move in a random manner over the time dimension and in non-random trends in the move dimension. Again, a trading rule was devised which obtained profits in excess of buy and hold. [Ref. 21]

> Stevenson and Bear (1970) found in their study of corn and soybean commodity futures prices that speculative prices move in a systematic as opposed to a random

manner. They found mechanical trading rules employing filters [5] based upon these trends could produce profits greater than a buy-and-hold policy would provide. [Ref. 22]

In their paper "The Information Content of Option Prices and a Test of Market Efficiency", Chiras and Manaster (1978) used actual option prices to calculate implied variances of future stock returns. They found a trading strategy based upon these variances yielded abnormal returns and concluded the Chicago Board of Exchange (CBOE) was inefficient in the pricing of options during the period of their study. [Ref. 23]

And finally, Rausser and Carter (1983), in their recent study of soybean future and spot prices, employed a number of forecasting techniques in attempting to predict future spot prices for soybeans and soybean oil, and found the CBOE futures price at planting time inefficient in that forecasting models were found which could better predict the future spot price. One of the more successful models employed was the Box-Jenkins or univariate Auto-Regressive Integrated Moving Average (ARIMA) model which employed only historical prices. [Ref. 24]

These and other studies may not yet be sufficient to disprove the Efficient Market Hypthosis. They are sufficiently rigorous to be considered as valid examples of exceptions to the hypthosis. Whether they are of adequate

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[5] Various mechanical trading rules based upon some percentage of price movement; e.g., if the price of a stock or commodity moves up x per cent from some base price such as first day observed, then buy it. If the price moves down by x per cent from its subsequent high, then sell it. The size of x defines the filter size. The rule can be employed in short sells as well.

number or what number of exceptions is necessary to disprove the hypthosis is best left to the financial economists.

E. RELEVANCE OF EMH TO FORECASTING

If the weak form of the Efficient Market Hypthosis were true without exception, the purpose of this thesis would be without hope of success. In fact, the preceding statement holds if any form is true without exception. An examination was made of each form of EMH because, as has been shown, if any form is valid the weak form is also valid. If EMH is true and holds always, it would be impossible to more accurately predict a future spot price of any commodity than the prediction made by the market through its futures prices. At any point in time the market would already have discounted all available information into present prices. It would also anticipate future prices by discounting the additional knowledge of inflation, projected supply and demand, market trends and cycles, etc. through the device of futures contracts. Clearly then, if EMH is valid, futures contracts must offer the best available prediction of the future price of any given commodity.

Business and government managers, dependent upon supplies of a commodity for the production of products or services, would therefore do best to base the volume of their purchases on the futures price established by the market; stockpiling when the futures price indicated steep future price increases, postponing purchase when the futures price indicated precipitous price declines were in store in future, and merely buying in accordance with demand when futures prices indicated little change was in store. Or, if it was appreciated that, although the futures price was the best forecast of future prices available, it was still far from accurate, managers might hedge their position by

purchase cf futures contracts. No other course wculd be logical in the absence of a more accurate forecast.

The Efficient Market Hypthosis is therefore directly relevant to the success of any attempt to forecast prices in a speculative market. Hopefully, sufficient excepticns have been found to each form of EMH to allow the intent of this thesis at least a theoretical possibility of success. Accordingly, effort will now be devoted toward selection of an appropriate forecast technique.

III. SELECTING A FORECAST TECHNIQUE

Many scientific forecasting techniques or models have been developed and refined over the years. Recent years have witnessed the development of numerous computer software statistical programs. Today, virtually all the more widely accepted forecast techniques are available for use on the computer. Consequently, forecasting is now much easier, faster, and accurate than in past when forecasts were largely undertaken only by statisticians through the use of calculators.

The available forecast techniques vary widely in complexity of concept, accuracy, ease of use, and applicability between different data sets or type forecast to be made. No one technique has proven superior for all situations or data types. Each forecast contemplated being attempted must therefore be examined to determine the most appropriate technique, or model, to employ.

This chapter will briefly examine several forecasting models and select the model best suited to the stated objective of forecasting medium term (one year or less into the future) commodity prices. The purpose is to show the logic behind the choice of the model which will be used, not to educate the reader upon statistical techniques. Accordingly, although a brief description of the concept involved in each model may be made, a modicum of statistical knowledge will be assumed to be held by the reader and no extended explanation of the various models will be attempted.

A. AVAILABLE FORECASTING TECHNIQUES

Forecasting techniques can be divided into two basic types: qualitative and quantitative. Qualitative methods are subjective in nature. They normally employ the opinion of experts to predict events at some distance into the future. They do not attempt to forecast specific levels or values of variables. They are long range forecasts of future trends, directions or probable developments in society, economics, markets, etc.

Quantitative methods analyze historical data in order to predict future values of some variable or variables of interest. Quantitative methods may be employed for forecasts of varying length into the future (lead time), from immediate or short range forecasts out to long range forecasts of from two to ten years. The intent of this paper is to forecast specific short to medium range future values of a specific variable (one to twelve months in this case). Quantitative methods are most appropriate to this purpose. Selection of a forecast method will therefore be made from the quantitative group of models.

All quantitative forecasting methods make use of the same basic strategy. They analyze past data, attempt to identify recurrent patterns in the data, associate those patterns with some trend or outcome, then extrapolate or extend current patterns into the future in order to forecast a future value. This strategy, of course, rests upon the assumption that the identified pattern will continue into the future and that the associated consequence is valid - i.e., has been correctly related to the pattern - and will again occur. If this assumption does not hold true no quantitative forecasting method will give accurate predictions. Since this is more likely to be valid in the short term than for the long term, it is not surprising short term forecasts

are normally more accurate than long term forecasts. [Ref. 25]

Quantitative forecast methods are of two types, causal and time series.

1. Causal Models

Causal models attempt to identify a variable or variables that are related to and believed to affect the variable to be predicted in some way. If the relationship between the identified variable(s) and the affected variable can be discerned, a model may be constructed which, hopefully, will duplicate that relationship. The identified variable(s) which cause a change in the affected variable are called the independent variable(s). The affected variable, the value of which is attempted to be forecast, is called the dependent variable. Once the relationship between the independent and dependent variables has been approximated and a model developed, the forecaster uses predicted values of the independent variable(s) to forecast future values of the dependent variable.

The main types of causal models are:

Multiple Regression:
An equation, called the regression equation, approximates the relationship between the independent variables and the dependent variable. Estimates are made of the values of the coefficients of the independent variables in the regression equation, then the regression equation is used to predict future values of the dependent variable. For instance, sales of a particular product might be the dependent variable, while product price, advertising expenditure level, size of sales force, and a competitors product price, sales force and advertising might be independent variables.

Econometrics:

Econometrics incorporates a larger number of independent variables into a forecast than does multiple regression. A very complex and involved method, instead of one regression equation, it uses systems of interrelated regression equations. Regression analysis is used to estimate the variable coefficients used in these equations. Econometric models attempt to express complex and intricate relations between numerous factors that affect the economy and the market, product, or other subject being forecast. Econometric models include macro economic factors national or international in scope along with local factors, or those more directly related to the forecast subject. For example, in order to predict a future price of a specific commodity, an econometric model would attempt to determine the relationship between several factors and their combined effect upon the commodity's price. That is, the model would attempt to simultaneously determine and simulate the effect of the factors upon one another as well as their effect upon the commodity's price. The effect of macro factors, such as interest rates, unemployment levels, money supply, and national inventory levels, as well as the effect of direct factors, such as weather and predicted crop size, both, upon one another and upon the commodity's price, would be treated.

Multivariate Box-Jenkins:

Whereas the univariate model (later described) requires and uses only historical values of the independent variable (which is itself being forecast) in order to make a forecast, the multivariate model, in addition, uses whatever independent variables identifiable as affecting the dependent variable. It attempts to approximate the actions of the independent variables upon the dependent variable by means of transfer functions [Ref. 25].

2. Time Series Models

Time series models analyze historical values of the variable being forecast in an effort to recognize data patterns and their subsequent effect upon the variable. The pattern is then extrapolated into the future to predict future values of the variable. This is the important distinction between causal and time series models. All causal models attempt to duplicate the effect of one or more independent variables upon the dependent variable. Time series models have no independent variables, their forecasts are based solely upon the historical patterns of the variable being forecast.

The users of time series models appreciate the existence of independent variables. They contend, however, that the result of the combined actions of all the independent variables is ultimately reflected in the value of the dependent variable and that future values of that variable are reflected in the past patterns of the same variable. Therefore, why attempt to discover the relationship between any number of independent variables and the dependent variable? It is a difficult task at best and error can occur if an independent variable exists which is not included in the model, or if the relationship between known variables is miscalculated. Further, even if all the important independent variables are recognized and their relationship to the dependent variable somewhat accurately depicted, those relationships are usually not static so that any laboriously gained accuracy may be fleeting. Why not circumvent that difficulty by only treating the variable being forecast, if such methods are available and relatively accurate?

Several widely used time series models are listed below. In all instances the term data refers to the historical value of the dependent variable, the variable being forecast.

Moving average:

Equation (3.1) represents a moving average.

$$F_{t+1} = (X_t + X_{t-1} + \ldots, X_{t-N+1})/N$$

(eqn 3.1)

Where: F = forecast value

X = historical data value for a specified period

N = number of data pericds observed

t = the most recent value observed

t + 1 = next cccurring period

t - 1 = previously occurred period

A simple moving average of the data values is used to predict future data values. For example, in order to predict the amount of shipments of a manufactured product expected for the next month, a six month moving average of monthly shipments might be used. The average of the six most recent monthly shipments would be calculated and used as the predicted number of shipments for the next month. Then, at the end of the following or predicted month, the number of shipments that actually occurred for that month would become one of the six values to be averaged and the oldest monthly value would be discarded. A new six month average is then calculated and becomes the prediction for the next month's shipments.

Such a simple moving average 'smoothes' the data by averaging the random errors. The number of observations, N, used in the calculations may be varied as desired but care must to be taken in selecting the size N to use. The greater the number of observations used the greater the smoothing effect. If N is too large, however, the average will fail tc detect trends. The predicted value will simply

tend towards the mean of the entire historical data set and the effect of the most recent data will be largely lost. Conversely, if N is too small then recently occurring fluctuations or "spikes" will be given too great an emphasis and inaccuracy will result.

Simple exponential smoothing:
In exponential smoothing an average is also maintained. It is assumed, however, that more recent data values or movements are stronger indicators of future levels than are older values. Accordingly, the average is weighted. An exponentially decreasing set of weights is assigned the data, with the most recent data value receiving the greatest weight, and its predecessors receiving increasingly less weight, till the oldest value receives the least.

Decomposition:
A time series may be considered to consist of at least four basic parts: seasonality, trend, cyclicality, and randomness. The time series is broken down so that the first three of these parts are identified and their values estimated and used to forecast future data values.

Box-Jenkins (ARIMA)
Box-Jenkins incorporates regression, moving average, exponential smoothing, and the seasonality and trend portions of decomposition into its equations. The time series is first differenced one or more times to remove trend and seasonality and achieve stationarity. An Auto Regressive Integrated Moving Average (ARIMA) model is then selected and fitted to the resultant data. The technique offers a rather large set of models from which may be selected that model which best represents or "fits" the data. (ARIMA procedures will be more throughly addressed shortly.)

B. MODEL SELECTION

As previously noted, no one method has been shown to work best for all situations and all data types. A model must be selected which is appropriate to the data. That task will now be accomplished, employing the following set of criteria for model selection:

1. Probable or possible model accuracy
2. Required operator statistical expertise
3. Available microcomputer software
4. Ease of use or application
5. Cost

The causal models all share some common characteristics. They all involve the use of independent variables which are regressed onto a dependent variable. Causal models are more complex and difficult to understand than time series models. They are generally more expensive and require more forecast preparation time then do time series models, especially the econometrics and multivariate Box-Jenkins models, which are respectively the most and second most expensive and time consuming in preparation of all the models thus far mentioned [Ref. 25].

Causal and time series models differ in the lead times they may forecast for. Considering lead times as follows:

immediate: less than one month
short term: one to three months
medium term: three months to two years
long term: greater than two years

Time series models may normally be used for immediate, short or medium term forecasts - at least out to one year. Causal models may normally be used for short, medium and some long term forecasting. For very long term forecasts qualitative methods must be used. [Ref. 26]

Both causal and time series models may be used for short term forecasts, with comparable accuracy. Time series models sometimes prove more accurate than causal models for the earlier stages of short term forecasting, but causal models are accurate in the middle and later stages of medium term forecasts. Although Univariate Box-Jenkins models have been successful in some cases for forecasts out to two years, causal models are normally more accurate for lead times of one year or longer, and really come into their own for medium and long term forecasts [Ref. 26].

Either method then, causal or time series, may be used for short or medium term forecasting (to one year) since both are accurate for those lead times. However, although both methods are plausible, the lesser complexity and cost and the general ease of application of the time series as a class, relative to the causal methods, allows the elimination of the entire class of causal methods from further consideration.

1. Time Series

Of the time series models noted, each offers certain advantages and disadvantages. The moving average is the simplest, least expensive, easiest and quickest to apply. These characteristics make it useful when a large number of items are to be forecast, such as would occur in many inventory situations. Unfortunately, it is also the least accurate of the methods.

Simple exponential smoothing offers a bit more accuracy than moving average but is still the least accurate of the remaining models. It is however, inexpensive to use, quick, easily understood, requires little data storage and is automatic, once a computer is programmed for it. Exponential smoothing may be used in situations where forecast error does not entail great risk and its lower cost may therefore be taken advantage of.

Decomposition is easier to understand and use than Box-Jenkins and better deals with cyclical components. It is less accurate than Box-Jenkins and, like Box-Jenkins, is not automatic. It too requires some interaction with the forecaster, in the form of interpretation and estimation.

Having successively ascended in accuracy with each of the time series models above noted, the most powerful model, Box-Jenkins, is is arrived at. Box-Jenkins is, however, the most difficult of the time series models to understand, requires the most time to prepare and is the most expensive. It also is not automatic and requires considerable intervention and interpretation on the part of the forecaster.

Computer programs for Box-Jenkins are available, however, including microcomputer programs. Although it may be the most expensive of the time series models to use in terms of computer time, the actual cost for computer time is negligible when employed on a microcomputer. Further, if it can be understood by the average business manager then it is not too complicated. Considering the risk normally entailed by forecast error for the subject variable of this paper, accuracy must take precedence over the other requirements. Box-Jenkins is therefore the method selected to be employed.

For a forecast period of one year Box-Jenkins should give an accuracy roughly comparable to that of the more expensive, complex and time consuming causal methods. It is the most accurate of the time series models and, hopefully, although the most complex, will prove sufficiently easy to understand and use to be employed by the average business manager with a Bachelor's degree in Business Administration, the level of statistical training held by the author. [Ref. 25]

C. BOX-JENKINS

Dependent upon one's perspective, the main advantage or disadvantage of Box-Jenkins is the requirement of determining the correct model to be employed, from a class of possible models. Unlike exponential smoothing, Box-Jenkins does not assume the model to be used with the data beforehand. A model must be chosen by the forecaster which is appropriate for the subject data.

Since the process is not automatic and requires some skill on the part of the forecaster, different forecasters may select different models. Business managers may consider this a disadvantage and it has perhaps inhibited the widespread use of Box-Jenkins in the business community.

The wide range of models available with Box-Jenkins and its procedure for selecting the model best representing the forecast data may also be considered an advantage for the accuracy achieved by the resultant forecast. Box-Jenkins may therefore become more widely used as more computer software becomes available, and the average manager becomes more conversant with the computer and more aware of the method and the benefits offered by its accuracy in situations where forecast error entails high risk. Notwithstanding the outcome of this paper, several areas exist where Box-Jenkins has proven accurate and worth the added cost relative to other time series models. Additional time and capital have recently been devoted to forecasting by medium and large businesses and use of ARIMA is on the increase with these organizations [Ref. 27]. Its uses by management have included forecasts for industry sales [Ref. 28], product line demand [Ref. 25], interest rates [Ref. 27] and product shipment levels [Ref. 29] and [Ref. 30]. [6]

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[6]In addition, these references offer other forecast type examples as well and are excellant sources for theory and application of the Box-Jenkins technique.

1. ARIMA Model Selection

Selection of the proper model consists of three phases: identification, estimation and testing, and application as represented in figure 3.1.

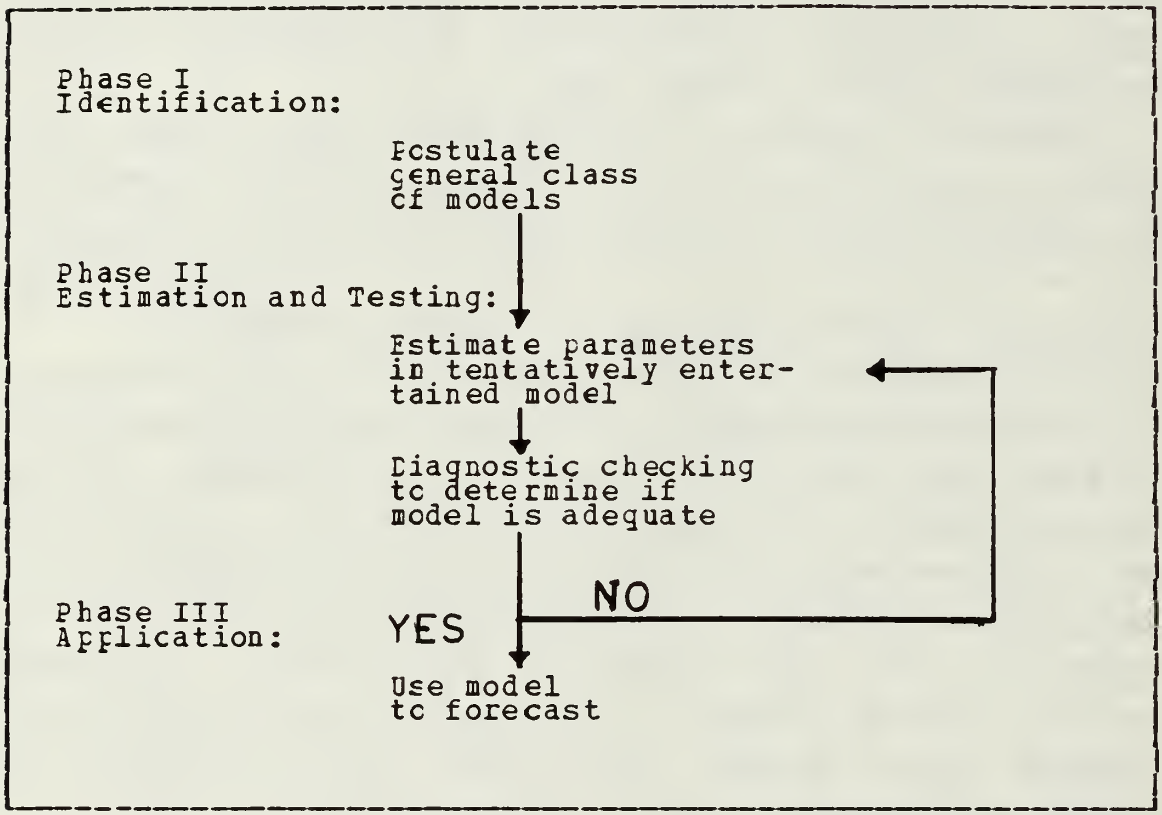

Figure 3.1 ARIMA Model Selection Procedure.

The Box-Jenkins method has three basic models, the Autoregressive (AR), Moving Average (MA), and Mixed Autoregressive Moving Average (ARMA) model.

The AR model develops a forecast based on a linear, weighted sum of previous data. The general AR model is represented by:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + e_t \qquad \text{(eqn 3.2)}$$

where: X_t is the forecast value,

X_i $(i = 1, 2, \ldots, p)$ is observed value at time i,

ϕ_i is the weighting coefficient for the pth previous period, and

e_t is the expected forecast error at time t.

The weights and e values are determined by using multiple regression analysis.

The Moving Average models forecast is a function of previous forecast errors. The general MA model is represented by:

$$X_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots \theta_q e_{t-q} \qquad \text{(eqn 3.3)}$$

Where: Xt is the forecast value,

e_{t-i} $(i = 1, 2, \ldots, q)$ is the forecast error at time t

θ_i $(i = 1, 2, \ldots, q)$ is a weighting coefficient for the qth previous period, which is calculated by a nonlinear least-squares method.

The third model, ARMA, is a combination of the first two and can be represented by:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots \phi_p X_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots \theta_q e_{t-q} \qquad \text{(eqn 3.4)}$$

The most useful characteristics of a time series for identifying the appropriate Box-Jenkins model are the autocorrelation function (acf) [7] and partial autocorrelation function (pacf). [8] Examination of acf and pacf plots allow the forecaster to discern whether the best model is AR(p), MA(q), or ARMA(p',q').

a. Stationarity

If a series is stationary [9] acf and pacf plots may be used to select a model. But business or economic series are often not stationary. Many, or most, contain trends or seasonality. This is especially true when the series is a level, such as prices or housing starts, rather than a rate of change or return.

Non-stationary series must be made stationary before a model may be selected and the procedure continued. The data is therefore differenced in order to remove trend and seasonality and achieve stationarity. A short difference may be taken, either once or twice, to remove trend, and a long difference, of twelve for monthly data, or four for quarterly data, taken to remove seasonality.

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[7] Autocorrelation: the lag k autocorrelation of a time series of n observations is the correlation between the observed value Z at time t, and the value at time t-k, calculated over pairs of times (k+1,1), (k+2,2),...,(n,n-k) exactly as the correlation between two distinct variables X and Y would be calculated.

[8] Partial Autocorrelation: the lag k partial autocorrelation of a time series W is essentially the estimated coefficient of W at time t-k in the regression of W at time t onto W at t-1, W at t-2,...W at t-k. It may be thought of as the autocorrelation between any two variables, Z at time t, and Z at t+k, seperated by a lag of k time units, with the effects of the intervening variables, Z at t+1, Z at t+2,...,Z at t+k-1 eliminated.

[9] A time series is considered stationary if the mean and variance are constant over time (and both are finite) and if the autocorrelation between values of the process at two time periods depends only on the distance between these time points and not on the time period itself.

Should a series be differenced d times before stationarity is achieved, and the resultant series is identified to be ARMA(p',q'), the original series is then said to be an integrated mixed autoregressive moving average, ARIMA(p',d,q').

b. Diagnostic checks

Once stationarity has been achieved and a model selected several diagnostic tests are employed to ensure the proper model has been chosen. When the user is sufficiently confident that all is in order the forecast is made.

D. ACCURACY

All data computation is performed by the computer once the historical data has been entered. The computer will, of course, compute and display the necessary plots, etc. at the users command. But the user must determine which plots are to be made, examine those plots and select the proper model based upon his interpretation of the data. The method is not automatic.

This is an important distinction and the reason some managers have been reluctant to learn and use Box-Jenkins. Sufficient model adequacy tests are available, however, to ensure the correct model has been selected. If these tests indicate an inadequate model, the model selection procedure is reinitiated and a new model is selected and checked.

Once managers realize the model testing procedures protect agaisnt use of an improper model they should gain confidence in ARIMA forecasting techniques and profit from its accuracy relative to other time series methods. Viewed from this perspective the large number of models available is, in fact, an attribute. [10]

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[10]Available models include: autoregressive (AR), moving

Accuracy is the main or, perhaps, the only attribute of Box-Jenkins relative to the other time series methods. It should be remembered, however, accuracy is that which is most desired in forecasts and should be pursued any time its benefits outweigh its costs.

In the following chapter several series of commodity prices will be analyzed and forecasts made utilizing the Box-Jenkins method.

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average (MA), mixed autoregressive moving average (ARMA) or autoregressive integrated moving average (ARIMA) of any combination of first or second order, one or two consecutive differences, with or without a seasonal difference.

IV. FORECAST RESULTS

Twenty four forecasts were made consisting of three one year forecasts for each of eight commodities. The results of each of the 24 computer forecast runs are presented in individual tables located in Appendix A. A summary of the total results of all 24 runs is presented in Table I, below.

A. DATA SOURCES, COMPUTER AND SOFTWARE USED

All commodity prices used were taken from the 1983 COMMODITY YEAR BOOK published by the Commodity Research Bureau, Inc. [Ref. 31] Box-Jenkins or ARIMA time series analysis and forecast techniques were used exclusively with the historical prices of each commodity as the sole data source. All forecasts were made utilizing an International Business Machines (IBM) Model 370 series mainframe computer with the MINITAB [11] data analysis computer software package and the MINITAB reference manual [Ref. 32]. Other software programs are available - such as Statistical Analysis System (SAS) [12] software - along with their subject reference manuals [Ref. 33]. which offer ARIMA for use on mainframe computers. In keeping with the stated purpose of evaluating a forecast system sufficiently inexpensive in purchase and implementation to be utilized by the managers of small businesses or government units with budgetary restrictions, a software program was selected which is capable of being run

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[11]MINITAB data analysis software may be purchased through MINITAB, 215 Pond Laboratory, University Park, PA 16802. Telephone (814)865-1595 Telex 842510. The program is available for use on microcomputers with as little as 256K RAM.

[12]SAS software is available through the SAS Institute Inc., PO Box 8000, Cary, North Carolina 27511

on mini or even microcomputers with as little as 256 thousand bytes of random access memory (256K RAM).

B. RESULTS

Each of the tables in Appendix A represents a forecast for a year's prices of the subject commodity. A forecast is made for each month and is presented next to the actual occurred value for that month. The Absolute Percentage Error (APE) is merely the absolute value of the difference between the value forecast for a particular month and the actual value which occured for that month. The Mean Absolute Percentage Error (MAPE) for a given period, e.g., the first three, six or nine months of a year, is the simple average or mean of the APE values for that period. MAPE figures were segmented into various quarterly combinations in order to examine differences in accuracy between different forecast periods within a years forecast.

Table I chronicles the MAPE values which occurred for each of the six periods covered in each of the 24 computer forecast runs. At the bottom of the table a simple average of the total MAPE figures for all 24 forecast runs is given. For example, the average value of the 24 MAPE's for the entire year is 6.72 percent.

Note the general trend of declining forecast accuracy over time, with the first quarter normally the most accurate, followed by the second and third, then the last quarter the least accurate. Although a declining trend in accuracy is discernable between each successive period, it is most pronounced following the first three months. A 46% increase in the MAPE (averaged for the 24 periods) occurs between the first three months and the first six months, from 4.36% to 6.72% respectively. The decline is slight thereafter, continuing until an approximate difference of

TABLE I

MAPE

MEAN ABSOLUTE PERCENTAGE ERRORS (MAPE)

	ENTIRE YEAR	FIRST THREE MONTHS	FIRST SIX MONTHS	FIRST NINE MONTHS	LAST SIX MONTHS	LAST THREE MONTHS
1980 ALUMINUM	01.58	00.83	00.95	01.77	02.21	01.02
1981 ALUMINUM	04.15	01.17	02.43	02.28	05.88	09.76
1982 ALUMINUM	00.71	00.19	00.29	00.65	01.12	00.88
1980 COAL	00.47	00.38	00.29	00.40	00.65	00.70
1981 COAL	02.19	00.19	00.59	01.67	03.80	03.77
1982 COAL	01.01	01.53	01.24	01.02	00.79	01.01
79-80 COTTON	05.44	02.47	03.96	05.69	06.91	04.67
80-81 COTTON	07.05	07.55	09.12	08.54	05.00	02.61
81-82 COTTON	07.14	09.07	10.69	09.33	03.59	00.55
'80 GASOLINE	08.04	07.53	10.80	08.70	05.28	06.05
'81 GASOLINE	02.28	01.23	01.43	01.31	03.13	05.18
'82 GASOLINE	03.98	01.91	06.85	04.82	01.10	01.45
1980 SOYBEAN	09.57	10.94	09.21	11.10	09.93	04.97
1981 SOYBEAN	06.13	08.01	06.99	06.90	05.27	03.82
1982 SOYBEAN	03.09	00.24	00.52	01.26	05.66	08.57
1980 STEEL	14.27	07.31	15.82	15.85	12.73	09.55
1981 STEEL	14.56	12.52	15.10	13.10	14.03	19.22
1982 STEEL	35.62	07.47	17.88	27.78	53.35	59.13
1980 TIN	03.30	03.47	03.00	02.37	03.60	06.11
1981 TIN	07.87	04.02	09.45	10.06	06.28	01.28
1982 TIN	08.28	09.81	12.67	10.46	03.90	01.75
1980 ZINC	03.34	01.87	01.98	02.78	04.71	05.03
1981 ZINC	04.82	02.17	03.36	05.24	06.28	03.58
1982 ZINC	06.49	02.80	08.78	07.35	04.20	03.91
AVERAGE VALUE OF EACH MAPE COLUMN	6.72	4.36	6.39	6.68	7.06	6.86

54% is realized between the averaged MAPE's of 4.36% for the first three months, and 6.72% for the yearly average. Which is to say, forecast accuracy suffers a 54% decline on average between the first three months and the year. This result is in consonance with the literature which, as previously noted, largely purports Box-Jenkins techniques to be most accurate over a short run period such as one to three months.

Since all time series methods are predicated upon the assumption that historical relationships will continue into the future and the farther one progresses into the future the less likely past relationships are to continue in their entirety, a declining accuracy over time is to be expected. The slight difference occurring between the second, third and last quarters' accuracy in the sample data is, however, noteworthy. The literature would have anticipated a steeper trend of decline, with a larger portion of the error occurring in the final quarter since, in ARIMA, the mean of the forecasts tends toward the mean of the data set as the number of forecast periods increases [Ref. 34]. Although this does not affect the experiment's outcome, it would be interesting to observe if the same would continue in another and larger data set.

Note also, the rather wide range of forecast accuracy or error which occurred. The most accurate yearly forecast had an MAPE of less than one percent while the least accurate yearly MAPE value was over 35 percent, with a rather large 59 percent MAPE occurring in the forecast for the final quarter of that year.

1. Caveat

As previously noted, Box-Jenkins is purported to be capable of making accurate forecasts for numerous time series of differing characteristics. It can manage quite well series with trend or seasonality. It can not, however, manage all series. Some series do not lend themselves well to ARIMA techniques. For instance, ARIMA does not perform well for series with heavy cyclicality [Ref. 25]. ARIMA accuracy is dependent upon achievement of stationarity and stationarity cannot be obtained when cyclical effects are too pronounced. While the autoregressive component will reflect some of the cyclical effect this reflection lags

behind the occurrence and as the cyclical effect increases so too is the forecast error likely to increase as well.

The forecasts for steel are believed to be a valid example of this ARIMA weakness. Selecting a model for this commodity was one of the more difficult model selections made, for each of the three years forecasted. The three forecasts for steel are the most inaccurate of the 24 yearly forecasts.

Although the data showed signs of cyclicality and model selection proved difficult, for reasons given below, forecasts for this commodity were decided to be attempted anyway. The first two forecasts, 1980 and 1981, each had MAPE of over 14% for the entire year. These were the least accurate to have occurred to that point but were not so far afield as to have been without value for a volatile commodity. However, the forecast for 1982 had a MAPE of over 35% for the year.

The Steel forecasts were included in the results as an example of a series for which ARIMA did not perform well. Although the first two forecasts were marginal in comparison to overall forecast results, the last forecast was considerably out of the established tolerance of accuracy. Such an occurance might well happen to a forecaster lulled into a false sense of confidence by previously accurate forecasts for other series. It was also considered well to assume other series of marginal characteristics probably exist that would give the average forecaster some difficulty. Accordingly, the Steel forecasts were included in the results.

It may also be assumed a forecaster might have sufficient cause to not attempt forecasts of a series with characteristics such as those of the subject Steel series. Accordingly, Table II depicts the averaged MAPE values for the 21 forecasts of the remaining seven commodities.

TABLE II

BEST 21 MAPE

AVERAGE MAPE FOR 21 BEST FORECASTS

ENTIRE YEAR	FIRST THREE MONTHS	FIRST SIX MONTHS	FIRST NINE MONTHS	LAST SIX MONTHS	LAST THREE MONTHS
4.62	3.68	4.98	4.94	4.25	3.65

Removal of the "outlier" Steel forecasts brings the average MAPE of the yearly forecasts from 6.72% to 4.62%; an impressive accuracy. Which is more likely correct? The answer perhaps lies between the two, or, it may in fact be larger than either figure. Note also, the averaged MAPE for the last quarter is approximately equal to that of the first quarter. This is an unexpected result. A larger data set would be most appreciated to see if it is an anomalous occurrence, specific to this data set.

The writer regrets sufficient time was not available for additional forecasts to have been made. A greater variety of commodities, covered over a larger range of time, would have been most welcome. None-the-less, as will be shown, sufficient variety of commodities, span of time, and number of forecasts attempted, is considered to have occurred to lend validity to the conclusions drawn in the following chapter.

V. SUMMARY, OBSERVATIONS AND CONCLUSIONS

A. SUMMARY

The stated intent of this thesis was to determine the plausibility of forecasting the price of commodities used in the production of goods and services one year into the future, with an average absolute accuracy of ten percent or less between the forecast and actual values occurring. Because the intended user of any potential forecast method selected is the small business or government manager without sufficient funds available to retain either a full time statistician or the services of a commodities forecasting firm, it was additionally stipulated the method must be employable with commonly available computer software, on mini or microcomputers. Finally, the method chosen was not to require statistical expertise greater than that considered to be held by the average Bachelor of Science of Business Administration graduate; the assumed level of statistical training of many, or most, business managers, and that of the author.

After devoting some attention to The Efficient Market Hypothosis, which stated that predictions of accuracy greater than those of "the market" were not possible, it was concluded there was sufficient doubt about the hypthosis to allow a prudent continuation of the effort.

A forecast method was then selected. Several forecast techniques were briefly examined. The advantages and disadvantages of each were highlighted and their characteristics and capabilities compared to those desired for the proposed technique. It was noted that time series methods are available with accuracy roughly comparable to causal methods for

lead times of up to one year. Causal methods were then eliminated from further consideration as too complicated, expensive, and time consuming to employ, thereby leaving several time series models as possible candidates.

Of these, the Box-Jenkins or Autoregressive Integrated Moving Average (ARIMA) technique was found to be the most accurate. The greatest potential drawback of ARIMA was considered to be its level of sophistication and complexity relative to the other possible time series candidates. However, since the author's statistical training is comparable to that of the intended users, successful assimilation and use by the author of any method satisfying the desired capabilities was therefore assumed to meet the stipulation regarding the level of user expertise as well.

The disadvantage of cost for ARIMA's relatively high consumption of computer time was considered to be largely negated by its availability in microcomputer software programming - a stipulated requirement. The larger overall time required by ARIMA to learn and use was considered to be more than offset by its advantage in accuracy. ARIMA was therefore selected to be the method employed.

Twenty four forecasts were then made; eight commodities were analyzed, with three seperate one year forecasts made for each. The Mean Absolute Percentage Error (MAPE) was calculated, recorded, and compiled for each forecast, in multiples of three month periods. The average MAPE value was found to be well within the desired accuracy of ten percent for all periods and when the "outlier" results of one commodity's forecasts were removed, the accuracy improved even further.

B. OBSERVATIONS

As indicated by the literature, Box-Jenkins is a complicated and involved technique. Its assimilation and understanding did not prove to be too great an obstacle, however, for the author. Therefore, since the author's statistical training is assumed to match that of the average business manager, Box-Jenkins can probably be understood by most managers, especially those with recent degrees in Business Administration.

Applying Box-Jenkins proved a greater challange than understanding its theory. Still, its application did not prove an insurmountable task and, again, it is not considered too formidable for the average manager.

The method does require considerable interpretation on the part of the user in selecting the appropriate model to be employed. The diagnostic checks normally afforded sufficient safeguard. Whenever the checks failed to distinguish one model as superior to another, there was usually little difference between the forecast results of the two. However, in isolated instances considerable difference did occur. Such occurence was rare enough to allow the above positive statement regarding the validity of the diagnostic checks to stand, but a caution is in order. Though infrequent, significant difference can occur between two models with seemingly equal diagnostic check results.

The computer program used was interactive, as opposed to batch, so that data manipulation and forecast results were essentially available instantaneously. This greatly facillitated the learning process. Data interpretation for model selection and testing became much easier as the experience level advanced.

This experiment was not conducted on a completely ex ante basis. For a few of the earlier forecasts attempted, it

was found improved results could be obtained by selection of an alternate model. In each such instance review of the data supported selection of the alternate model. This early and overall isolated practise facillitated learning. For any experiment conducted totally with historical data the temptation to review and reinitiate experiment procedures is great. In this case, it is not considered to have materially affected the forecast results or any conclusions drawn from those results. While the forecaster in a real situation would not have the benefit of assessing a models results before a forecast was made, forecasts could be continually compared with real values as they occurred and a new model selected early on if the original proved lacking in accuracy. It is, in fact, suggested that any potential forecaster should make extended practise of analyzing data series, selecting models, making forecasts and comparing the results to historical data, in order to gain proficiency in model selection.

It was found a model could not be selected for a commodity price forecast for one year and be assumed to remain the best model for the succeeding year for the same commodity. Occurring changes in trend, seasonality, the economy, etc. will, at times, cause another model to better represent the data.

ARIMA software is available which will select the model automatically, thus internalizing model identification to the computer and relieving the forecaster of that task. [13] However, this process of letting the computer do the thinking for you is strongly disavowed by Box and Jenkins. It might conceivably be of use to a manager in need of producing numerous forecasts for similar products or regions

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[13] Automatic model selecting software may be obtained through David P. Reilly, Automatic Forecasting Systems, Statistical Consultants, P.O. Box 563, Hatboro, PA. 19040.

in a short amount of time and when accuracy is of less consequence. In those cases automatic software might possibly make Box-Jenkins as quick and easy to use as some of the simpler time series methods while, hopefully, retaining at least a measure of its accuracy.

Forecasts should be reviewed for accuracy and updated on a quarterly basis. Regardless of the accuracy obtained, the newly occurred values should be added to the data set and new forecasts made. Recalling, ARIMA gives greater weight to the most recently occurring values because those values are more likely to be highly related to the values which are about to occur. Quarterly updates will therefore receive the benefit of increased or, at a minimum, retained forecast accuracy. It should be stressed data examination for possible model change is an important part of this quarterly review and update.

If an inappropriate model is employed, the relatively high accuracy occurring in the first quarter of even inappropriate models, should still allow a moderately accurate yearly forecast, if the new data is added to the series in quarterly model review and forecast updates.

C. CONCLUSIONS

Commodity price forecasts incorporating Box-Jenkins techniques can offer budgeting efficiencies to the small business or small budget manager dependent upon commodities for the production of goods or services. At a minimum, more accurate budgets will be obtained than budgets made without forecasts, or those made using forecasts consisting largely of the "feelings" of experienced managers.

ARIMA techniques can be learned and utilized by the average manager, on inexpensive microcomputers, using commonly available software.

Although the results obtained in the experiment conducted in this paper were within the stated goal, further research is needed in order to determine whether or not Box-Jenkins forecasts could be the basis for increased profits through the purchase of futures contracts.

A suggested method would be to amass a history of futures contract prices for a set of commodities, say one year in future from the contracts base date. The average absolute difference between the price forecast by the futures contract and the market price actually occurring one year later would represent the accuracy of futures contracts. A comparison of futures contract price accuracy for commodity prices one year in the future could then be made with the accuracy of Box-Jenkins forecasts for the same commodities and period. Assuming a sufficiently large data set were used, if Box-Jenkins forecasts proved more accurate than futures contracts then reduction of risk and improved profit should be obtainable.

Such an effort would be a logical and welcome continuation of the study initiated in this paper. The accuracy here obtained by a beginning student of Box-Jenkins further suggests that it would have at least the possibility of succeeding.

Notwithstanding further study, examples herein cited of present uses of Box-Jenkins indicate it could be profitably utilized by many small business managers, and the results of this study indicate an additional use, in budgeting for commodity prices.

APPENDIX A

COMPUTER FORECAST RUN RESULTS

TABLE III

1980 ALUMINUM

FORECAST FOR 1980 AVERAGE ALUMINUM PRICE
IN CENTS PER POUND:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	66.8599	66.2500	0.92057
FEB	67.5117	66.8600	0.97480
MAR	67.9880	68.4000	0.60230
APR	69.0049	70.5200	2.14848
MAY	69.6867	70.0000	0.44756
JUN	70.4300	70.0000	0.61436
JUL	71.2564	70.0000	1.79483
AUG	72.5344	70.0000	3.62061
SEP	73.3523	70.0000	4.78906
OCT	74.6551	75.6500	1.31516
NOV	75.1222	76.0000	1.15499
DEC	75.5437	76.0000	0.60035

ARIMA 0 2 1, 0 1 1, 12 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	0.9301	0.0829	11.22
2	SMA 12	0.8015	0.2112	3.80

DIFFERENCING:
2 REGULAR 1 SEASONAL DIFFERENCE OF ORDER 12

NO. OF OBSERVATIONS:
ORIGINAL SERIES 60 AFTER DIFFERENCING 46

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 1.58%
FIRST THREE MONTHS = 0.83%
FIRST SIX MONTHS = 0.95%
FIRST NINE MONTHS = 1.77%
LAST SIX MONTHS = 2.21%
LAST THREE MONTHS = 1.02%

TABLE IV

1981 ALUMINUM

FORECAST FOR 1981 AVERAGE PRICE OF ALUMINUM
IN CENTS PER POUND:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	75.9661	76.0000	0.0446
FEB	76.5566	76.0000	0.7324
MAR	78.0710	76.0000	2.7250
APR	80.1679	76.0000	5.4841
MAY	79.6237	76.9000	3.5419
JUN	79.6000	78.0000	2.0513
JUL	79.5760	78.0000	2.0206
AUG	79.5521	78.0000	1.9899
SEP	79.5282	78.0000	1.9593
OCT	85.1543	78.0000	9.1722
NOV	85.4804	78.0000	9.5902
DEC	85.4564	77.3200	10.5230

ARIMA 1 2 0, 0 1 0, 12 USED.
FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	AR 1	-0.4229	0.1200	-3.52

DIFFERENCING:
2 REGULAR 1 SEASONAL DIFFERENCE OF ORDER 12

NO. OF OBSERVATIONS:
ORIGINAL SERIES 72 AFTER DIFFERENCING 58

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 4.15%
FIRST THREE MONTHS = 1.17%
FIRST SIX MONTHS = 2.43%
FIRST NINE MONTHS = 2.28%
LAST SIX MONTHS = 5.88%
LAST THREE MONTHS = 9.76%

TABLE V

1982 ALUMINUM

FORECAST FOR 1982 AVERAGE PRICE OF ALUMINUM IN CENTS PER POUND.

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	76.7609	76.5000	0.34104
FEB	76.4537	76.5000	0.06052
MAR	76.6284	76.5000	0.16781
APR	77.0817	76.5000	0.76039
MAY	76.6843	76.5000	0.24089
JUN	76.6439	76.5000	0.18809
JUL	76.0492	76.5000	0.58921
AUG	75.4543	76.5000	1.36693
SEP	74.8594	76.5000	2.14457
OCT	77.0645	76.0000	1.40064
NOV	76.6429	76.0000	0.84594
DEC	75.7048	76.0000	0.38836

ARIMA 1 2 0, 1 1 0, 12 USED.
FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	AR 1	-0.4165	0.1106	-3.77
2	SAR 12	-0.4956	0.1368	-3.62

DIFFERENCING:
2 REGULAR 1 SEASONAL DIFFERENCES OF ORDER 12

NO. OF OBS:
ORIGINAL SERIES 84 AFTER DIFFERENCING 70

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 0.71%
FIRST THREE MONTHS = 0.19%
FIRST SIX MONTHS = 0.29%
FIRST NINE MONTHS = 0.65%
LAST SIX MONTHS = 1.12%
LAST THREE MONTHS = 0.88%

TABLE VI

1980 COAL

FORECAST FOR 1980 BITUMINOUS COAL:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	460.226	459.100	0.245204
FEB	461.757	459.400	0.513152
MAR	463.294	461.600	0.367004
APR	464.836	464.400	0.093892
MAY	466.383	465.900	0.103599
JUN	467.935	465.900	0.436770
JUL	469.492	466.700	0.598241
AUG	471.055	467.800	0.695785
SEP	472.622	470.200	0.515177
OCT	474.195	469.600	0.978486
NOV	475.773	474.000	0.374092
DEC	477.356	473.800	0.750663

ARIMA 0 2 1 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	0.8278	0.0833	9.94

DIFFERENCING: 2 REGULAR

NO. OF OBSERVATIONS:
ORIGINAL SERIES 48 AFTER DIFFERENCING 46

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 0.47%
FIRST THREE MONTHS = 0.38%
FIRST SIX MONTHS = 0.29%
FIRST NINE MONTHS = 0.40%
LAST SIX MONTHS = 0.65%
LAST THREE MONTHS = 0.70%

TABLE VII

1981 COAL

FORECAST FOR 1981 BITUMINOUS COAL:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
1	475.141	476.000	0.18034
2	476.488	477.900	0.29538
3	477.839	478.300	0.09637
4	479.193	483.400	0.87025
5	480.552	484.400	0.79447
6	481.914	488.200	1.28766
7	483.280	501.900	3.70997
8	484.649	503.200	3.68651
9	486.023	506.800	4.09957
10	487.401	506.000	3.67567
11	488.782	507.600	3.70713
12	490.168	510.200	3.92630

ARIMA 0 2 1 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	0.8384	0.0717	11.70

DIFFERENCING: 2 REGULAR

NO. OF OBSERVATIONS:
ORIGINAL SERIES 60 AFTER DIFFERENCING 58

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 2.19%
FIRST THREE MONTHS = 0.19%
FIRST SIX MONTHS = 0.59%
FIRST NINE MONTHS = 1.67%
LAST SIX MONTHS = 3.80%
LAST THREE MONTHS = 3.77%

TABLE VIII

1982 COAL

FORECAST FOR 1982 BITUMINOUS COAL:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	512.910	520.600	1.47708
FEB	515.635	525.300	1.83982
MAR	518.375	525.000	1.26195
APR	521.128	527.900	1.28272
MAY	523.897	529.600	1.07678
JUN	526.680	529.300	0.49488
JUL	529.479	533.900	0.82804
AUG	532.292	534.900	0.48755
SEP	535.120	537.300	0.40572
OCT	537.963	533.900	0.76096
NOV	540.821	536.200	0.86178
DEC	543.694	536.200	1.39764

ARIMA 0 2 1 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	0.8681	0.0595	14.58

DIFFERENCING: 2 REGULAR

NO. OF OBSERVATIONS:
ORIGINAL SERIES 72 AFTER DIFFERENCING 70

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 1.01%
FIRST THREE MONTHS = 1.53%
FIRST SIX MONTHS = 1.24%
FIRST NINE MONTHS = 1.02%
LAST SIX MONTHS = 0.79%
LAST THREE MONTHS = 1.01%

TABLE IX

1979-80 COTTON

FORECAST FOR 1979-80 AVERAGE SPOT COTTON
IN CENTS PER POUND:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
AUG	62.7569	62.4700	0.4592
SEP	65.2614	62.5400	4.3515
OCT	64.9188	63.2800	2.5898
NOV	68.3096	63.8100	7.0516
DEC	68.0259	66.5800	2.1717
JAN	67.6006	72.7800	7.1165
FEB	70.8968	81.0500	12.5271
MAR	71.2040	79.6300	10.5815
APR	75.9769	79.4400	4.3594
MAY	77.9025	78.6600	0.9630
JUN	76.4141	72.8000	4.9645
JUL	72.9761	79.4000	8.0906

ARIMA 0 1 1, 0 1 0, 18 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	-0.3425	0.1004	-3.41

DIFFERENCING:
1 REGULAR   1 SEASONAL DIFFERENCE OF ORDER 18

NO. OF OBSERVATIONS:
ORIGINAL SERIES 108   AFTER DIFFERENCING 89

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 5.44%
FIRST THREE MONTHS = 2.47%
FIRST SIX MONTHS = 3.96%
FIRST NINE MONTHS = 5.69%
LAST SIX MONTHS = 6.91%
LAST THREE MONTHS = 4.67%

TABLE X

1980-81 COTTON

FORECAST FOR 1980-81 AVERAGE SPOT COTTON
IN CENTS PER POUND:

MONTHN	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
AUG	81.2810	86.0000	5.4872
SEP	79.8310	87.9100	9.1901
OCT	79.3070	86.1800	7.9752
NOV	77.6264	87.4500	11.2334
DEC	77.7785	87.6300	11.2421
JAN	77.3685	85.5700	9.5845
FEB	77.0121	83.7000	7.9903
MAR	75.7678	81.9200	7.5101
APR	76.1130	81.5500	6.6670
MAY	77.0781	78.8600	2.2596
JUN	75.6964	78.5200	3.5960
JUL	76.9772	75.4800	1.9836

ARIMA 0 2 2, 0 1 1, 12 USED

FINAL ESTIMATES OF PARAMETERS

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	0.6148	0.0341	18.01
2	MA 2	0.3923	0.0607	6.46
3	SMA 12	0.9143	0.0724	12.63

DIFFERENCING:
2 REGULAR 1 SEASONAL DIFFERENCES OF ORDER 12

NO. OF OBSERVATIONS:
ORIGINAL SERIES 120 AFTER DIFFERENCING 106

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 7.05%
FIRST THREE MONTHS = 7.55%
FIRST SIX MONTHS = 9.12%
FIRST NINE MONTHS = 8.54%
LAST SIX MONTHS = 5.00%
LAST THREE MONTHS = 2.61%

TABLE XI

1981-82 COTTON

FORECAST FOR 1981-82 AVERAGE SPOT COTTON PRICE IN CENTS PER POUND:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
AUG	70.9148	66.8400	6.0964
SEP	68.5250	61.2200	11.9324
OCT	66.6927	61.0800	9.1891
NOV	63.9949	57.9100	10.5075
DEC	64.0969	55.5200	15.4484
JAN	64.6271	58.2400	10.9668
FEB	64.9873	57.7000	12.6296
MAR	63.5422	60.1200	5.6922
APR	63.3672	62.4100	1.5337
MAY	63.2130	62.8200	0.6256
JUN	61.0633	61.4800	0.6778
JUL	61.7188	61.5000	0.3558

ARIMA 0 2 2, 1 1 1, 12 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	SAR 12	-0.2474	0.1037	-2.38
2	MA 1	0.5709	0.0903	6.32
3	MA 2	0.3067	0.0916	3.35
4	SMA 12	0.9011	0.0698	12.91

DIFFERENCING:
2 REGULAR 1 SEASONAL DIFFERENCE OF ORDER 12

NO. OF OBSERVATIONS:
ORIGINAL SERIES 132 AFTER DIFFERENCING 118

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 7.14%
FIRST THREE MONTHS = 9.07%
FIRST SIX MONTHS = 10.69%
FIRST NINE MONTHS = 9.33%
LAST SIX MONTHS = 3.59%
LAST THREE MONTHS = 0.55%

TABLE XII

1980 GASOLINE

FORECAST FOR 1980 AVERAGE WHOLESALE PRICE OF GASOLINE (REGULAR GRADE - LEADED):

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
1	482.225	481.100	0.2338
2	471.681	517.500	8.8539
3	484.694	560.400	13.5092
4	491.039	585.400	16.1191
5	511.083	595.500	14.1758
6	527.420	598.600	11.8910
7	550.879	601.100	8.3548
8	574.707	602.900	4.6763
9	596.691	599.600	0.4851
10	611.368	591.500	3.3589
11	644.768	590.800	9.1348
12	629.827	596.100	5.6580

ARIMA 1 2 0, 1 1 0, 12 USED.
FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	AR 1	-0.6205	0.1860	-3.34
2	SAR 12	-0.4832	0.1568	-3.08

DIFFERENCING:
2 REGULAR   1 SEASONAL DIFFERENCES OF ORDER 12

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 8.04%
FIRST THREE MONTHS = 7.53%
FIRST SIX MONTHS = 10.80%
FIRST NINE MONTHS = 8.70%
LAST SIX MONTHS = 5.28%
LAST THREE MONTHS = 6.05%

TABLE XIII

1981 GASOLINE

FORECAST FOR 1981 AVERAGE WHOLESALE PRICE OF GASOLINE (REGULAR GRADE - LEADED):

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	612.567	607.500	0.83406
FEB	646.857	632.900	2.20525
MAR	687.663	683.200	0.65330
APR	705.196	694.700	1.51085
MAY	704.236	690.400	2.00408
JUN	694.950	685.600	1.36375
JUL	685.082	677.400	1.13402
AUG	674.560	668.400	0.92166
SEP	658.593	666.400	1.17150
OCT	637.807	666.100	4.24748
NOV	625.396	661.700	5.48647
DEC	619.460	657.700	5.81416

ARIMA 0 2 1, 0 1 0, 12 USED.
FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	0.6120	0.1001	6.12

DIFFERENCING:
2 REGULAR, 1 SEASONAL DIFFERENCES OF ORDER 12

NO. OF OBS: ORIGINAL SERIES 84, AFTER DIFFERENCING 70

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 2.28%
FIRST THREE MONTHS = 1.23
FIRST SIX MONTHS = 1.43%
FIRST NINE MONTHS = 1.31%
LAST SIX MONTHS = 3.13%
LAST THREE MONTHS = 5.18%

TABLE XIV

1982 GASOLINE

FORECAST FOR 1982 AVERAGE WHOLESALE PRICE OF GASOLINE, (REGULAR GRADE- LEADED):

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	654.027	651.700	0.3571
FEB	650.376	642.300	1.2575
MAR	646.746	621.100	4.1292
APR	643.137	578.600	11.1540
MAY	639.546	555.700	15.0884
JUN	635.977	582.700	9.1431
JUL	632.427	628.800	0.5768
AUG	628.897	636.300	1.1635
SEP	625.386	628.400	0.4795
OCT	621.896	617.200	0.7608
NOV	618.425	611.000	1.2152
DEC	614.972	600.700	2.3760

ARIMA (0 2 1) USED.
FINAL ESTIMATES OF PARAMETERS

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	0.4452	0.0929	4.79

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE TWELVE MONTHS = 3.98%
FIRST THREE MONTHS = 1.91%
FIRST SIX MONTHS = 6.85%
FIRST NINE MONTHS = 4.82%
LAST SIX MONTHS = 1.10%
LAST THREE MONTHS = 1.45%

TABLE XV

1979-80 SOYBEANS

FORECAST FOR 1979-80 AVERAGE PRICE OF NO. 1 YELLOW SOYBEANS:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
OCT	724.210	656.	10.3978
NOV	740.982	652.	13.6475
DEC	710.244	653.	8.7663
JAN	691.338	636.	8.7009
FEB	671.597	642.	4.6101
MAR	662.385	607.	9.1245
APR	689.154	580.	18.8196
MAY	680.919	604.	12.7350
JUN	689.982	610.	13.1118
JUL	693.875	722.	3.8955
AUG	728.728	745.	2.1842
SEP	741.245	813.	8.8259

ARIMA 0 2 1, 0 1 0, 18 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	0.9897	0.0076	131.04

DIFFERENCING:
2 REGULAR 1 SEASONAL DIFFERENCES OF ORDER 18

NO. OF OBSERVATIONS:
ORIGINAL SERIES 108 AFTER DIFFERENCING 88

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 9.57%
FIRST THREE MONTHS = 10.94%
FIRST SIX MONTHS = 9.21%
FIRST NINE MONTHS = 11.10%
LAST SIX MONTHS = 9.93%
LAST THREE MONTHS = 4.97%

TABLE XVI

1980-81 SOYBEANS

FORECAST FOR 1980-81 AVERAGE PRICE OF NO. 1
YELLOW SOYBEANS:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
OCT	791.013	827.	4.3515
NOV	782.170	891.	12.2143
DEC	830.700	773.	7.4644
JAN	823.933	757.	8.8419
FEB	782.792	734.	6.6475
MAR	754.751	737.	2.4086
APR	701.216	772.	9.1689
MAY	694.883	758.	8.3268
JUN	693.895	713.	2.6796
JUL	673.835	736.	8.4463
AUG	678.186	694.	2.2787
SEP	639.321	644.	0.7266

ARIMA 0 2 1, 0 1 0, 18 USED

FINAL ESTIMATES OF PARAMETERS

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	0.9888	0.0071	138.43

DIFFERENCING:
2 REGULAR 1 SEASONAL DIFFERENCE OF ORDER 18

NO. OF OBSERVATIONS:
ORIGINAL SERIES 120 AFTER DIFFERENCING 100

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 6.13%
FIRST THREE MONTHS = 8.01%
FIRST SIX MONTHS = 6.99%
FIRST NINE MONTHS = 6.90%
LAST SIX MONTHS = 5.27%
LAST THREE MONTHS = 3.82%

TABLE XVII

1981-82 SOYBEANS

FORECAST FOR 1981-82 AVERAGE CASH PRICE OF NO. 1 YELLOW SOYBEANS:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
OCT	630.483	630.	0.0766
NOV	626.699	628.	0.2071
DEC	625.628	623.	0.4218
JAN	625.322	630.	0.7425
FEB	625.233	624.	0.1975
MAR	625.205	616.	1.4943
APR	625.194	642.	2.6177
MAY	625.189	656.	4.6968
JUN	625.185	631.	0.9216
JUL	625.181	620.	0.8356
AUG	625.177	573.	9.1058
SEP	625.172	540.	15.7727

ARIMA 1 1 0 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	AR 1	0.2836	0.0843	3.36

DIFFERENCING: 1 REGULAR

NO. OF OBSERVATIONS:
ORIGINAL SERIES 132 AFTER DIFFERENCING 131

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 3.09%
FIRST THREE MONTHS = 0.24%
FIRST SIX MONTHS = 0.52%
FIRST NINE MONTHS = 1.26%
LAST SIX MONTHS = 5.66%
LAST THREE MONTHS = 8.57%

TABLE XVIII

1980 STEEL

FORECAST FOR 1980 AVERAGE WHOLESALE PRICE OF NO. 1 HEAVY MELTING STEEL SCRAP:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	90.4824	96.140	5.8847
FEB	90.2501	99.000	8.8383
MAR	90.0183	97.000	7.1976
APR	89.7871	90.540	0.8316
MAY	89.5565	69.620	28.6362
JUN	89.3266	62.240	43.5196
JUL	89.0971	67.450	32.0936
AUG	88.8683	77.950	14.0068
SEP	88.6401	87.240	1.6049
OCT	88.4124	92.220	4.1288
NOV	88.1854	97.290	9.3582
DEC	87.9590	103.680	15.1630

ARIMA 0 2 2 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	0.5835	0.0769	7.59
2	MA 2	0.4218	0.0994	4.24

DIFFERENCING: 2 REGULAR

NO. OF OBSERVATIONS:
ORIGINAL SERIES 84 AFTER DIFFERENCING 82
STORAGE AVAILABLE 40000

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 14.27%
FIRST THREE MONTHS = 7.31%
FIRST SIX MONTHS = 15.82%
FIRST NINE MONTHS = 15.85%
LAST SIX MONTHS = 12.73%
LAST THREE MONTHS = 9.55%

TABLE XIX

1981 STEEL

FORECAST FOR 1981 AVERAGE WHOLESALE PRICE OF NO. 1 HEAVY MELTING STEEL SCRAP:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	92.4467	95.000	2.6877
FEB	82.7489	91.110	9.1769
MAR	78.1347	105.140	25.6851
APR	77.5596	107.550	27.8851
MAY	81.1214	97.500	16.7986
JUN	80.6636	88.000	8.3368
JUL	84.2295	88.450	4.7716
AUG	85.9947	97.760	12.0349
SEP	83.5391	92.520	9.7070
OCT	77.3113	82.640	6.4481
NOV	58.9415	75.000	21.4113
DEC	52.2445	74.410	29.7883

ARIMA 1 2 1, 0 1 0, 18 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	AR 1	0.3689	0.1172	3.15
2	MA 1	0.9646	0.0588	16.39

DIFFERENCING:
2 REGULAR 1 SEASONAL DIFFERENCE OF ORDER 18

NO. OF OBSERVATIONS:
ORIGINAL SERIES 96 AFTER DIFFERENCING 76

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 14.56%
FIRST THREE MONTHS = 12.52%
FIRST SIX MONTHS = 15.10%
FIRST NINE MONTHS = 13.10%
LAST SIX MONTHS = 14.03%
LAST THREE MONTHS = 19.22%

TABLE XX

1982 STEEL

FORECAST FOR 1982 AVERAGE WHOLESALE PRICE OF NO. 1 HEAVY MELTING STEEL SCRAP:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
1	74.2085	83.0000	10.5922
2	74.0964	78.6300	5.7657
3	74.0052	69.7800	6.0550
4	73.9188	63.8600	15.7513
5	73.8336	58.3000	26.6443
6	73.7490	51.7700	42.4552
7	73.6647	49.0000	50.3361
8	73.5805	51.7300	42.2395
9	73.4963	48.9500	50.1457
10	73.4123	47.8600	53.3896
11	73.3285	45.0000	62.9523
12	73.2449	45.4800	61.0485

ARIMA 1 2 1 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	AR 1	0.2312	0.0951	2.43
2	MA 1	0.9814	0.0060	162.30

DIFFERENCING: 2 REGULAR

NO. OF OBSERVATIONS:
ORIGINAL SERIES 108 AFTER DIFFERENCING 106

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 35.62%
FIRST THREE MONTHS = 7.47%
FIRST SIX MONTHS = 17.88%
FIRST NINE = 27.78%
LAST SIX MONTHS = 53.35%
LAST THREE MONTHS = 59.13%

TABLE XXI

1980 TIN

FORECAST FOR 1980 AVERAGE PRICE OF TIN:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	837.793	836.460	0.1594
FEB	837.793	866.390	3.3007
MAR	837.793	900.230	6.9357
APR	837.793	872.210	3.9460
MAY	837.793	861.840	2.7902
JUN	837.793	845.190	0.8752
JUL	837.793	836.950	0.1007
AUG	837.793	834.610	0.3814
SEP	837.793	861.920	2.7992
OCT	837.793	832.920	0.5851
NOV	837.793	788.670	6.2286
DEC	837.793	751.360	11.5036

ARIMA 0 1 1 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	-0.2508	0.1071	-2.34

DIFFERENCING: 1 REGULAR

NO. OF OBSERVATIONS:
ORIGINAL SERIES 84 AFTER DIFFERENCING 83

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 3.30%
FIRST THREE MONTHS = 3.47%
FIRST SIX MONTHS = 3.00%
FIRST NINE MONTHS = 2.37%
LAST SIX MONTHS = 3.60%
LAST THREE MONTHS = 6.11%

TABLE XXII

1981 TIN

FORECAST FOR 1981 AVERAGE PRICE OF TIN:

COLUMN	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
1	684.119	739.940	7.5439
2	702.098	705.760	0.5189
3	719.396	691.700	4.0041
4	740.006	677.380	9.2453
5	754.109	652.070	15.6485
6	781.720	652.770	19.7544
7	786.845	680.220	15.6751
8	814.945	746.060	9.2331
9	846.754	777.360	8.9269
10	820.391	798.700	2.7157
11	810.633	813.000	0.2912
12	794.970	801.590	0.8258

ARIMA 1 1 0, 0 1 0, 18 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	AR 1	0.4208	0.1047	4.02

DIFFERENCING:
1 REGULAR 1 SEASONAL DIFFERENCE OF ORDER 18

NO. OF OBSERVATIONS:
ORIGINAL SERIES 96 AFTER DIFFERENCING 77

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 7.87%
FIRST THREE MONTHS = 4.02%
FIRST SIX MONTHS = 9.45%
FIRST NINE MONTHS = 10.06%
LAST SIX MONTHS = 6.28%
LAST THREE MONTHS = 1.28%

TABLE XXIII

1982 TIN

FORECAST FOR 1982 AVERAGE PRICE OF TIN:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	795.501	787.410	1.0276
FEB	793.975	749.930	5.8733
MAR	820.244	669.510	22.5142
APR	792.760	649.580	22.0419
MAY	750.688	662.350	13.3372
JUN	715.190	643.000	11.2272
JUL	704.326	638.000	10.3960
AUG	671.796	636.330	5.5735
SEP	658.413	644.330	2.1858
OCT	644.784	627.940	2.6824
NOV	620.691	627.930	1.1528
DEC	621.358	630.180	1.3999

ARIMA 1 1 0, 0 1 0, 18 USED

FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	AR 1	0.4045	0.0974	4.15

DIFFERENCING:
1 REGULAR 1 SEASONAL DIFFERENCE OF ORDER 18

NO. OF OBSERVATIONS:
ORIGINAL SERIES 108 AFTER DIFFERENCING 89

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 8.28%
FIRST THREE MONTHS = 9.81%
FIRST SIX MONTHS = 12.67%
FIRST NINE MONTHS = 10.46%
LAST SIX MONTHS = 3.90%
LAST THREE MONTHS = 1.75%

TABLE XXIV

1980 ZINC

FORECAST FOR 1980 ZINC, AVERAGE PRICE,
PRIME WESTERN SLAB, CENTS PER POUND:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	37.7374	37.5000	0.63314
FEB	37.8280	38.7000	2.25317
MAR	37.8625	38.9200	2.71702
APR	37.8757	38.5000	1.62155
MAY	37.8807	37.5000	1.01514
JUN	37.8826	36.5500	3.64587
JUL	37.8833	35.5000	6.71348
AUG	37.8835	35.9800	5.29058
SEP	37.8836	37.4600	1.13093
OCT	37.8837	38.4800	1.54971
NOV	37.8837	39.6900	4.55103
DEC	37.8837	41.6300	8.99909

ARIMA (1 1 0) USED.
FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	AR 1	0.3808	0.0899	4.23

DIFFERENCING: 1 REGULAR
NO. OF OBS:
ORIGINAL SERIES 108, AFTER DIFFERENCING 107

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 3.34%
FIRST THREE MONTHS = 1.87%
FIRST SIX MONTHS = 1.98%
FIRST NINE MONTHS = 2.78%
LAST SIX MONTHS = 4.71%
LAST THREE MONTHS = 5.03%

TABLE XXV

1981 ZINC

FORECAST FOR 1981 ZINC, AVERAGE PRICE, PRIME WESTERN SLAE, CENTS PER POUND:

MONTH	FORECAST	ACTUAL	APE
JAN	42.4311	41.6300	1.9243
FEB	42.7025	41.6300	2.5764
MAR	42.9748	42.1300	2.0053
APR	43.2480	43.7300	1.1022
MAY	43.5220	46.5500	6.5048
JUN	43.7969	46.6300	6.0757
JUL	44.0727	46.6700	5.5653
AUG	44.3493	49.7400	10.8378
SEP	44.6268	49.8800	10.5317
OCT	44.9051	46.4100	3.2425
NOV	45.1844	46.7500	3.3489
DEC	45.4644	43.6500	4.1568

ARIMA (0 2 2) USED.
FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	MA 1	0.5992	0.0849	7.06
2	MA 2	0.3779	0.0871	4.34

DIFFERENCING: 2 REGULAR
NO. OF OES:
ORIGINAL SERIES 120 AFTER DIFFERENCING 118

MEAN ABSCLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 4.82%
FIRST THREE MONTHS = 2.17%
FIRST SIX MONTHS = 3.36%
FIRST NINE MONTHS = 5.24%
LAST SIX MONTHS = 6.28%
LAST THREE MONTHS = 3.58%

TABLE XXVI

1982 ZINC

FORECAST FOR 1982 ZINC, AVERAGE PRICE,
PRIME WESTERN SLAB, CENTS PER POUND:

MONTH	FORECAST	ACTUAL	ABSOLUTE PERCENTAGE ERROR
JAN	42.5616	43.3100	1.7281
FEB	42.1736	43.5600	3.1826
MAR	42.0346	43.5600	3.5018
APR	41.9847	36.3900	15.3743
MAY	41.9668	36.6400	14.5381
JUN	41.9603	36.6900	14.3644
JUL	41.9580	38.8600	7.9721
AUG	41.9571	40.0000	4.8928
SEP	41.9568	42.2100	0.5998
OCT	41.9567	42.5000	1.2783
NOV	41.9567	40.8000	2.8350
DEC	41.9566	38.9900	7.6088

ARIMA (1 1 0) USED.
FINAL ESTIMATES OF PARAMETERS:

NUMBER	TYPE	ESTIMATE	ST. DEV.	T-RATIO
1	AR 1	0.3595	0.0837	4.30

DIFFERENCING. 1 REGULAR
NO. OF OBS:
ORIGINAL SERIES 132 AFTER DIFFERENCING 131

MEAN ABSOLUTE PERCENTAGE ERROR:
ENTIRE YEAR = 6.49%
FIRST THREE MONTHS = 2.80%
FIRST SIX MONTHS = 8.78%
FIRST NINE MONTHS = 7.35%
LAST SIX MONTHS = 4.20%
LAST THREE MONTHS = 3.91%

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